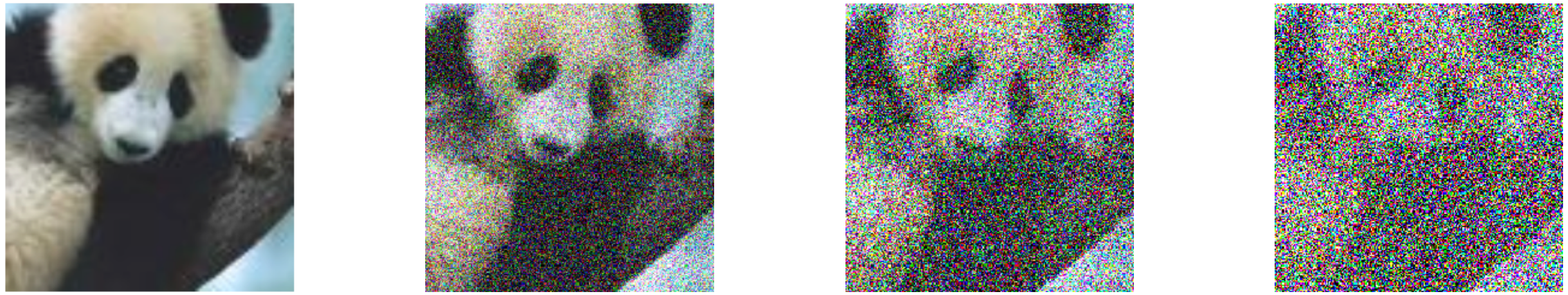
Certified Adversarial Robustness via Randomized Smoothing



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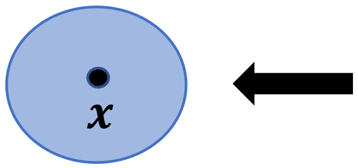
Introduction

We study a <u>**certified**</u> adversarial defense in ℓ_2 norm which <u>**scales**</u> to ImageNet

Background:

- Many adversarial defenses have been "broken"
- A *certified* defense (in ℓ_2 norm) is a classifier which returns *both* a prediction *and* a certificate that the prediction is constant within an ℓ_2 around the input



Certify that every prediction inside this ball will be "panda."

- Most certified defenses don't scale to networks of realistic size

Prior work on randomized smoothing

- Randomized smoothing was proposed as a certified defense by [1]
- The analysis was improved upon by [2]
- Our main contribution is the *tight* analysis of this algorithm

[1] M. Lecuyer, V. Atlidakis, R. Geambasu, D. Hsu, and S. Jana. "Certified Robustness to Adversarial Examples with Differential Privacy," IEEE S&P 2019.

[2] B. Li, C. Chen, W. Wang, and L. Carin. "Second-Order Adversarial Attack and Certifiable Robustness," arXiv 2018.

Randomized smoothing

- First, train a neural net f (the "base classifier") with Gaussian data augmentation:

clean image

corrupted by Gaussian noise

- Then, *smooth* f into a new classifier g (the "smoothed classifier"), defined as follows:

Randomized smoothing

$g(\boldsymbol{x})$ = the most probable prediction by f of random Gaussian corruptions of $\boldsymbol{x}$

Example: consider the input $\boldsymbol{x}$ = 

Suppose that when f classifies $\mathcal{N}(\boldsymbol{x}, \sigma^2 I)$ ,

🐼 is returned with probability 0.80
🐒 is returned with probability 0.15
🐱 is returned with probability 0.05

Then $g(\boldsymbol{x})$ = 🐼

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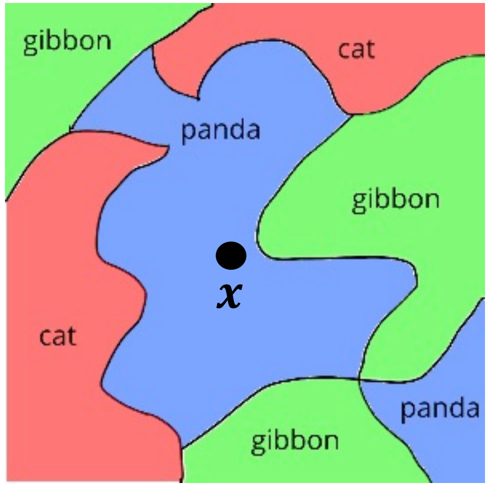

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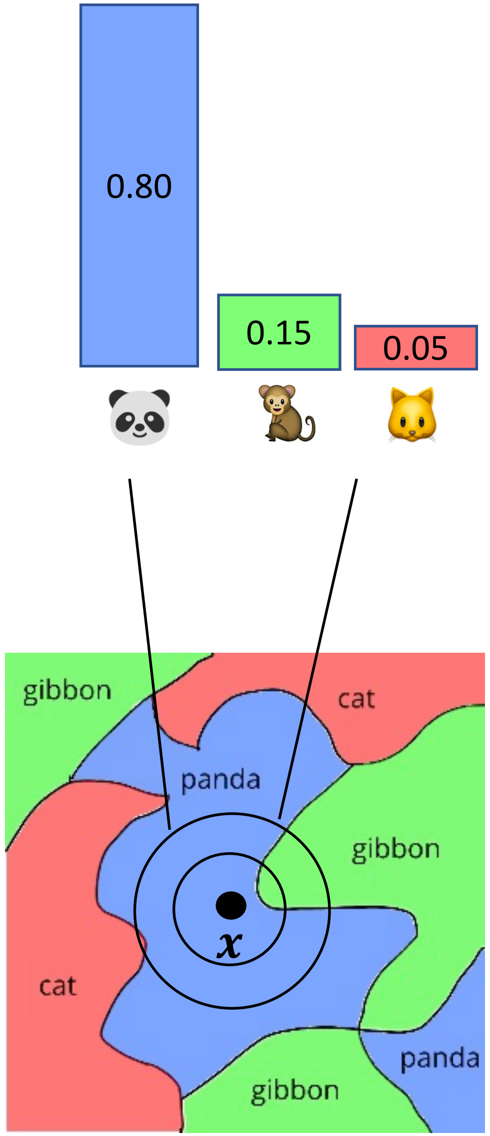
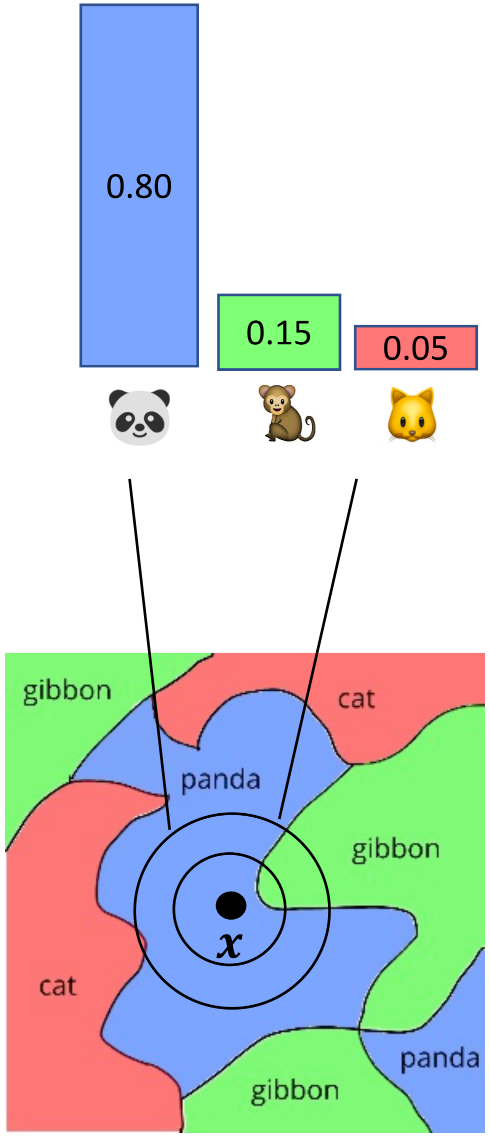


Class probabilities vary slowly

If we shift this Gaussian, the probabilities of each class can't change by too much.

Therefore, if we know the class probabilities at the input $\boldsymbol{x}$, we can *certify* that for sufficiently small perturbations of $\boldsymbol{x}$, the 🐼 probability will remain higher than the 🐒 probability.

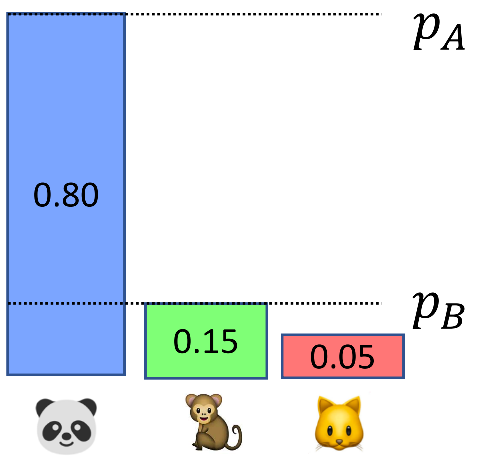


Robustness guarantee (main result)

- Let p_A be the probability of the top class (🐼)
- Let p_B be the probability of the runner-up class (🐒).
- Then g provably returns the top class 🐼 within an ℓ_2 ball around $\boldsymbol{x}$ of radius

$$R = \frac{\sigma}{2}(\Phi^{-1}(p_A) - \Phi^{-1}(p_B))$$

where Φ^{-1} is the inverse standard Gaussian CDF.

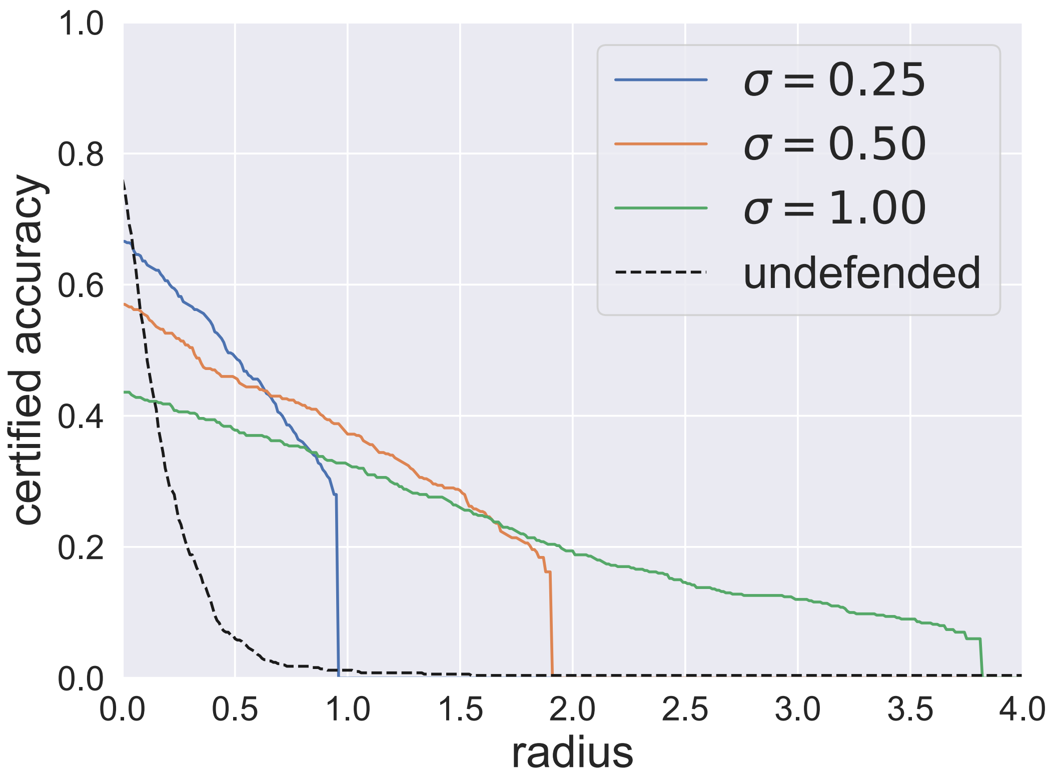


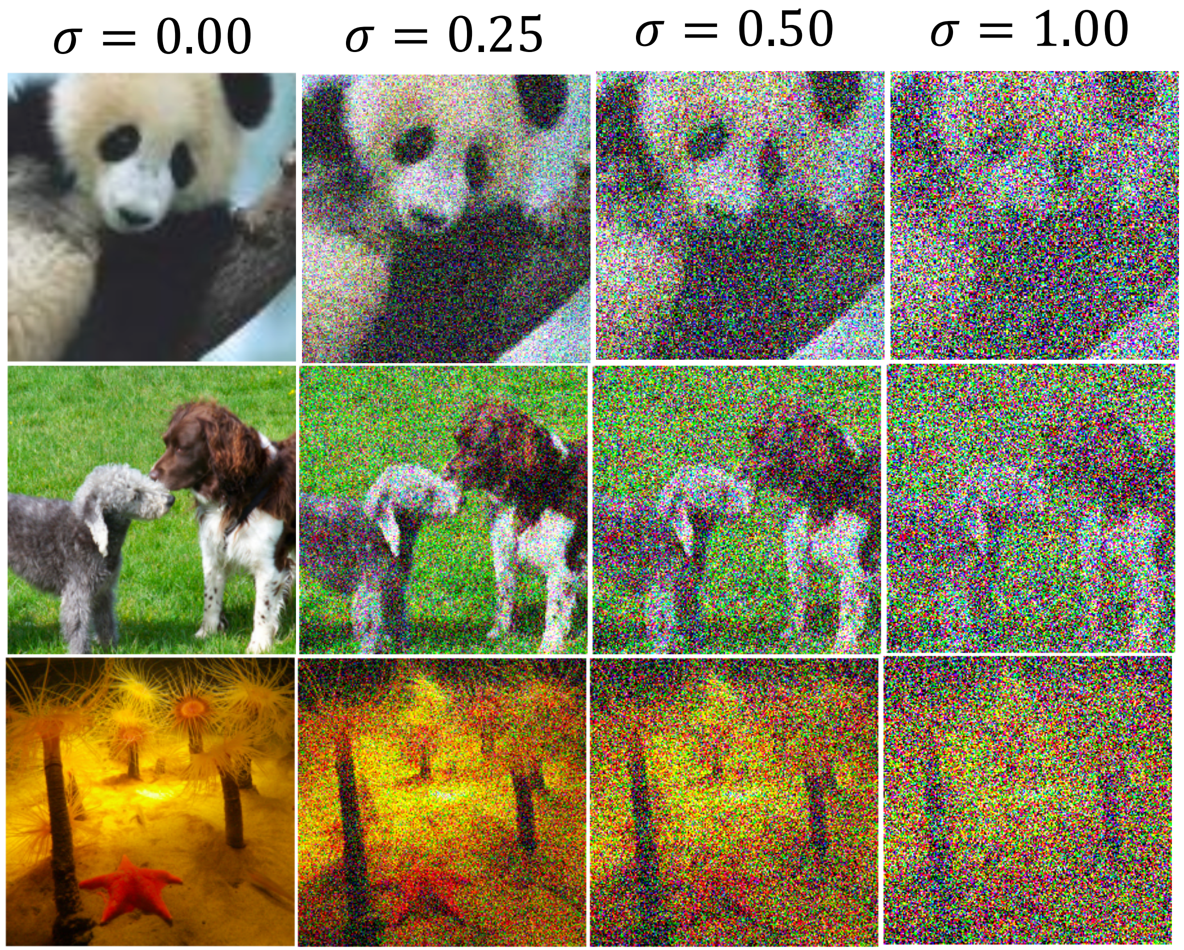
There's one catch

- When f is a neural network, it's not possible to exactly
    - evaluate the smoothed classifier
    - certify the robustness of the smoothed classifier

- However, by sampling the prediction of f under Gaussian noise, you can obtain answers guaranteed to be correct with arbitrarily high probability

ImageNet performance





Note: the certified radii are much smaller than this noise.

Thanks for listening!

Poster #64,   6:30 PM – 9:00 PM tonight

Code and trained models:
`http://github.com/locuslab/smoothing`